# Deterministic vs. Stochastic Calibration of Energy Simulation Model for an Existing Building

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## ABSTRACT

Building performance simulation tools have been widely used for performance assessment, optimal design & control, fault detection/diagnosis, energy retrofit, etc. However, many studies (IBPSA 1987-2013) have reported that there still exists a significant performance gap between the reality and simulation output, partly caused by unknown simulation inputs. Therefore, model calibration has been widely used to estimate unknown inputs. However, calibration attempts in area of building simulation may fail due to the following reasons: [1] uncertainty in simulation inputs, [2] sensor errors, and [3] long sampling time in data measurement. This paper addresses the abovementioned issues for reliable simulation prediction. In this study, an existing office building was selected. This study presents two calibration approaches: deterministic vs. stochastic calibration. Deterministic calibration finds a set of unknown values which minimize the difference between the measured data and simulation outputs. Stochastic calibration is based on Bayesian approach and finds probability distribution of each unknown input. Since stochastic calibration is computation-demanding, a Gaussian Process Emulator (GPE) was introduced in this study as a surrogate model of the EnergyPlus model. It is shown that the stochastically calibrated model can predict better than the deterministically calibrated model and can reduce the variance of unknown inputs. In addition, the accumulated measured data with a sampling time as long as a day might be unsuitable for calibration work due to lack of 'time-series trend'. This paper also pointed out the difference in calibration results when different sensor errors (-3%, 0%, +3%) exist and propose a future work to take it into account.

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**KEYWORDS**

Model calibration, Bayesian theory, Gaussian Process Emulator, Monte Carlo simulation

## INTRODUCTION

Building Performance Simulation (BPS) tools have been widely used for detection and diagnosis of system errors, energy retrofit, optimal design, optimal control, what-if scenario analysis, etc. However, the BPS tools still have difficulties and limitations due to loss and change of building information harvested from drawings and specifications. This leads to subjective judgment and assumptions based on simulationists' past knowledge and experience, and then it could increase a performance gap between the reality and simulation prediction.

To deal with this issue, model calibration has been widely used to estimate unknown inputs which minimize the gap between the reality and simulation outputs. This paper presents pros and cons of two different calibration approaches (deterministic vs. stochastic). For this study, EnergyPlus was chosen to describe an existing office. The Mean Bias Error (MBE) and the Coefficient of Variance of the Root Mean Square Error (CVRMSE) (ASHRAE Guideline 14 2002) were used to examine the calibrated model.

## ISSUSES IN MODEL CALIBRATION

Model calibration improves accuracy and robustness of a simulation model by estimation of unknown inputs. However, it should be noted that the calibration results are influenced by the quality of the initial model or 'uncalibrated model'. Thus, it is important to develop the initial model as accurate as possible through acquisition of reliable data from drawings, specification, interviews, site-visit, etc. In addition, some of simulation inputs are of highly stochastic nature (e.g. infiltration, occupant schedule) and hence are not easily quantified in a deterministic fashion.

A stochastic calibration technique based on Bayesian approach can provide probability distribution of uncertain inputs. Since stochastic calibration deals with probabilistic characteristics of simulation inputs and outputs, the stochastic approach is computation-demanding compared to the deterministic approach. To alleviate computation time, a Gaussian Process Emulator (GPE), which is regarded as a surrogate model of the dynamic whole-building simulators (e.g. EnergyPlus, TRNSYS, etc.), are used in this study.

There are only few studies reported which dealt with relevance of sensor errors, sampling time and aggregated energy to calibration work. Even though MBE and CVRMSE are widely used to validate a simulation model, it is still not good enough since they are based on a simple comparison in terms of monthly (or hourly) aggregated energy consumption. Even though the aggregated sum of building energy use is identical to model prediction, each sub-energy consumer (cooling, heating, lights, equipment, etc.) can be different from model prediction. However, it is very rare that existing buildings sub-meter each energy consumer. In addition, such comparison between the model and the reality should be based on not only MBE and CVRMSE but also be based on a dynamic pattern or 'time series trend'.

## TARGET BUILDING

In this study, a 5-storey office building (floor area: 6,900 $m^2$) located in South Korea was selected as shown in Figure 1. The HVAC system consists of 5 Constant Air Volumes (CAVs) for the interior zones of each floor and Fan Coil Units (FCUs) for the perimeter air-conditioning. The building plant consists of 2 absorption chillers and 2 cooling towers.

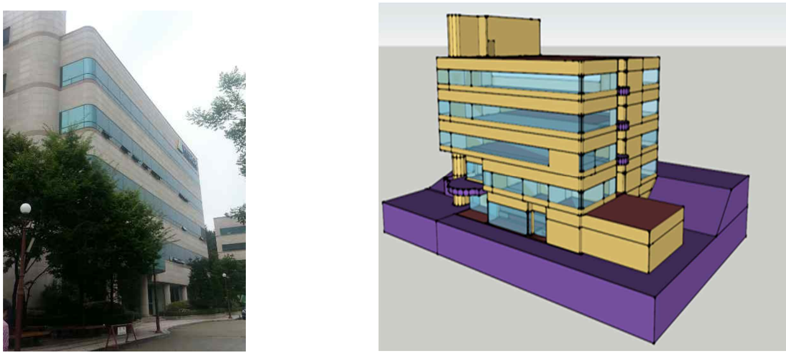


***Figure 1.*** *Target building (left) and EnergyPlus displayed in OpenStudio (right)*

At first, the simulation information was collected from drawings and specifications. Since the building was completed 17 years ago, many changes were made to the building. Lighting fixtures in the building were newly replaced with high-efficient ones. In addition, thermal properties of building materials, system efficiency of mechanical systems, COP of chillers, etc. must be carefully determined since systems and plants have deteriorated since their installments. During the modeling task, the authors encountered missing information with regard to building operation (setpoint temperatures, the amount of outdoor air intakes, etc.) and schedules (people, lights, equipment). Such information was hinted through several site-visits, walk-throughs, and interviews with building operators. In addition, the authors used information gathered from Building Energy Management System (BEMS) installed in the building. The buildings' operation conditions and schedules (e.g. HVAC turn-on/off time) were different from traditional schedules (ASHRAE 2013, DOE 2013). In other words, simulation inputs needs to be calibrated.

## GAUSSIAN PROCESS EMULATOR (GPE)

Since stochastic calibration is computation demanding, the authors used a surrogate model or GPE for EnergyPlus. The GPE is a linear regression model based on a training dataset, Gaussian process, and Bayesian inference. A general development process is as follows: (1) obtaining a training dataset, (2) developing Gaussian process regression model, (3) applying Bayesian inference to estimate hyperparameters, and (4) validation of the model.

In order to generate a training dataset for GPE, Latin Hypercube Sampling (LHS) method was selected. The number of sampling by LHS method was set to 500 (400 for GPE and 100 for validation). With the training dataset, the GPE was developed using Gaussian process, resulting in a linear regression model with Gaussian noise. The regression model has three unknown hyperparameters such as scale parameter, length-scale parameter, and error parameter. To estimate the hyperparameters, Maximum A Posteriori (MAP), one of Bayesian inference methods, was used.

Table 1 shows a comparison between EnergyPlus and GPE in terms of MBE and CVRMSE. The GPE is close to prediction by EnergyPlus. In particular, the GPE takes about 5 seconds of computation time while the EnergyPlus model takes about 5 days when uncertainty analysis was performed.

***Table 1.*** *Comparison between EnergyPlus and GPE*

| Methods | Heat extraction of AHU1 | Gas energy consumption |
|---|---:|---:|
| MBE (%) | - 0.01 | 0.02 |
| CVRMSE (%) | 0.04 | 0.03 |

## MODEL CALIBRATION AND VALIDATION

Based on previous studies (IBPSA 1989 – 2013), the authors identified probability ranges of uncertain inputs and categorized them into three: architecture, fans/pumps, and plants. The total number of uncertain inputs was 107. Inputs relevant to HVAC system were not included as uncertain inputs since most HVAC inputs could be obtained from drawings, site visits, an existing ESCO report, and HVAC manufacturer’s website.

The screening method can quantify the correlation between inputs and outputs, and were used to identify inputs having significant influence on outputs. In this paper, the factorial sampling method proposed by Morris (1991) was used. The Morris method is a one factor at a time (OAT) approach and ranks uncertain inputs in order of importance. As a result, a total of 29 significant inputs were selected.

The infiltration rate, the rated condenser pump head, and the coefficients in cooling capacity function of temperature curve were identified as most significant inputs to total energy demand for architecture, fans/pumps’ electricity energy consumption, and plant’s gas energy consumption, respectively.

For deterministic calibration, the authors used the ‘fmincon’ function in MATLAB Optimization Toolbox. For stochastic calibration, Bayesian approach was employed to estimate the posterior distribution of inputs.

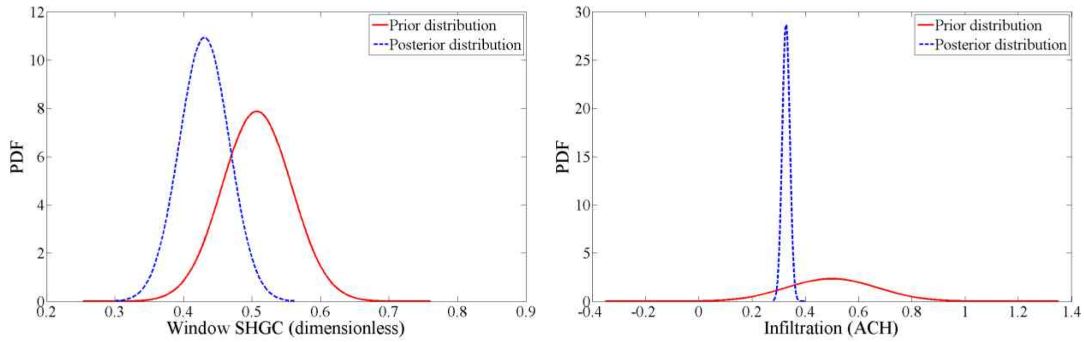
The calibration was conducted in two steps as follows: (1) 1$^{st}$ calibration: calibrating unknown inputs in areas of architecture and fans (objective function: heat extraction rate of AHU #1), and (2) 2$^{nd}$ calibration: with the use of inputs obtained from 1$^{st}$

calibration, the unknown inputs in the pump and the plant were estimated (objective function: gas energy consumption of absorption chiller). For calibration, the authors used the measured data during four days (July 5, 9, 10, and 11).

Table 2 and Figure 2 show calibration results and the prior and posterior distributions of two selected inputs.

***Table 2.*** *Calibration results (deterministic vs. stochastic)*

| Unknown inputs | | Deterministic | | Stochastic calibration | | | |
|---|---|---|---|---|---|---|---|
| | | Uncalibrated | Calibrated | Priors | | Posteriors | |
| | | | | Mean | STDEV | Mean | STDEV |
| Concrete | Conductivity | 1.491 | 1.394 | 1.491 | 0.3 | 1.4958 | 0.24 |
| | Density | 2179 | 2248.2 | 2179 | 149 | 2247.8 | 140.6 |
| | Specific Heat | 864 | 1039.4 | 864 | 92 | 937.28 | 75.3 |
| Mortar | Density | 1782 | 1789.5 | 1782 | 145 | 1805.3 | 105.9 |
| Insulation | Conductivity | 0.04 | 0.038 | 0.04 | 0.01 | 0.0412 | 0.01 |
| Boards | Density | 704 | 720.99 | 704 | 379 | 709.68 | 287.1 |
| | Specific Heat | 1359 | 1371.3 | 1359 | 615 | 1561.3 | 559.4 |
| Window | U-factor | 3.09 | 3.338 | 3.09 | 0.3094 | 3.2881 | 0.31 |
| | SHGC | 0.51 | 0.301 | 0.51 | 0.0507 | 0.4306 | 0.04 |
| Infiltration | ACH (1/hour) | 0.5 | 0.333 | 0.5 | 0.17 | 0.3279 | 0.01 |
| Fraction of person per area | | 1.0 | 0.5000 | 1.0 | 0.1 | 0.9457 | 0.07 |
| Fraction of light heat gains | | 1.0 | 0.5001 | 1.0 | 0.1 | 0.8322 | 0.09 |
| Fraction of equipment heat gains | | 1.0 | 0.5000 | 1.0 | 0.1 | 0.7218 | 0.05 |
| Supply fan | Pressure rise | 600 | 580 | 600 | 6 | 598.51 | 4.99 |
| Return fan | Pressure rise | 600 | 580 | 600 | 6 | 600.28 | 5.01 |
| Pump (Condenser) | Pump head | 180000 | 180000 | 20000 | 400 | 20031 | 384.04 |
| Pump (CHW) | Pump head | 180000 | 179997 | 20000 | 400 | 19951 | 386.39 |
| Absorption Chiller/Heater #1 | 1 / COP | 0.84 | 0.77 | 0.97 | 0.097 | 0.873 | 0.0624 |
| Absorption Chiller/Heater #2 | 1 / COP | 0.84 | 0.84 | 0.97 | 0.097 | 0.980 | 0.0937 |
| Cooling capacity function of temperature curve | Coefficient 4 | 0.209 | 0.2089 | 0.209 | 0.00418 | 0.209 | 0.0041 |
| | Coefficient 5 | -0.0056 | -0.0056 | -0.006 | 0.000113 | -0.006 | 0.0001 |
| | Coefficient 6 | 0.0094 | 0.0093 | 0.009 | 0.000189 | 0.009 | 0.0002 |
| | Coefficient 7 | -0.08 | -0.0801 | -0.08 | 0.001603 | -0.0799 | 0.0015 |
| Part load ratio Curve | Maximum value of x | 1.0 | 1.0 | 1.0 | 0.02 | 1.0001 | 0.0209 |
| Fuel input to cooling output ratio function of temperature curve | Coefficient 1 | 1.312 | 1.3115 | 1.312 | 0.026239 | 1.3082 | 0.0261 |




(a) SHGC of window (b) Infiltration rate

***Figure 2.*** *Comparison between priors and posteriors (For want of space, only two inputs were shown here.)*

It can be inferred that Solar Heat Gain Coefficient (SHGC) was decreased due to dirt accumulation on the glass surface. Based on the tracer gas test method conducted to the building, the average infiltration rate was 0.33 (ACH), which is close to the estimated value. The estimated fractions ('calibrated') of indoor heat gains (people, lights, equipment) were also less than values from literature ('uncalibrated'). The actual building is not operated at the maximum load due to frequent movement of occupants and irregular switching (on/off) of lights and appliances (Table 2).

The calibration results for pumps and plants show that the difference between the uncalibrated and calibrated model is insignificant, in contrast to the calibration results for architecture and fan. Coefficient of Variation (CV=STDEV/Mean) is defined as a standard deviation divided by a mean value. The greater CV, the greater the uncertainty (or risk) of the model is. The average CVs with regard to heat extraction rate of AHU #1 (sampling time = 10 minutes) and gas energy consumption of absorption chillers (sampling time = 1 day) are 0.0158 (1,221[$W$]/77,318[$W$]) and 0.0667 (106[$kWh$]/1,589[$kWh$]), respectively. In other words, the uncertainty of the absorption chillers is four times as high as that of AHU #1. This can be inferred that the data with a larger sampling time is disadvantageous for reliable calibration work.

Table 3 and Figure 3 show validation results by comparing the measured data to prediction outputs in terms of heat extraction rate of AHU #1. Be noted that the data used for validation (July 16, 22, and 23) were different from the data used for calibration (July 5, 9, 10, and 11). In general, both of the calibrated models predicts accurate (please refer to case #2 in Table 3). In order to investigate relevance of sensor errors to prediction accuracy, the authors arbitrarily assumed that there could be -3% (refer to case #1) and + 3% (refer to case #3) sensor errors. So far, there hasn't been studied yet how sensor errors could influence calibration work, but needs more investigation as a future study.

***Table 3.****Validation results and relevance of sensor errors to prediction (Case #1: assuming -3% sensor errors, Case #2: 0% sensor errors, Case #3: +3% sensor errors)*

| Methods | | Case #1 | **<u>Case #2</u>** | Case #3 |
|---|---|---|---|---|
| Deterministic | MBE (%) | 4.53 | **<u>7.39</u>** | 10.09 |
| | CVRMSE (%) | 10.73 | **<u>12.13</u>** | 13.88 |
| Stochastic | MBE (%) | -0.25 | **<u>-3.26</u>** | -6.45 |
| | CVRMSE (%) | 10.62 | **<u>11.20</u>** | 12.60 |

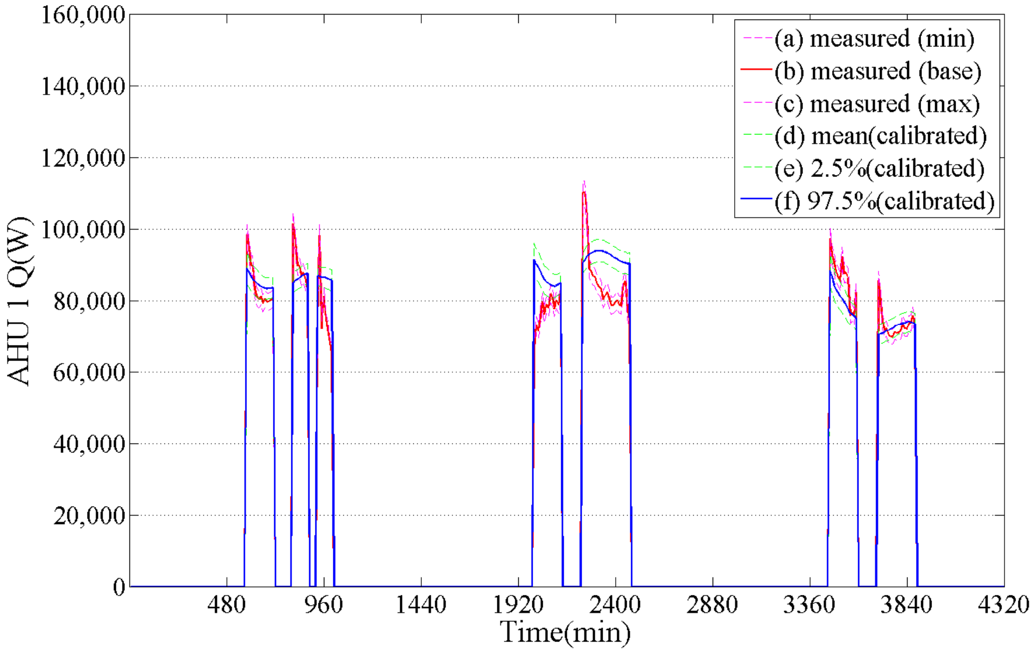



***Figure 3.*** *Validation of stochastic calibration (corresponding to Case #2 in Table 3)*

## CONCLUSIONS

This paper addresses two calibration approaches (deterministic vs. stochastic). Calibration work can be influenced by [1] uncertainty in simulation inputs, [2] sensor errors and [3] long sampling time of observation. To address the issues, a five-story office building was selected and two calibration approaches (deterministic, stochastic) were implemented. For stochastic calibration, the authors used GPE as a surrogate of EnergyPlus model.

As a result, the stochastically calibrated model can predict better than the deterministically calibrated model and can reduce the variance of unknown inputs.

In addition, please be noted that it would be difficult to obtain precise calibration results for gas energy consumption which is based on daily data. In other words, the accumulated measured data with the sampling time as long as a day (24 hours) might be unsuitable for calibration work due to lack of 'time-series trend'.

This paper also pointed out the difference in calibration results between the cases of different sensor errors (-3%, 0%, +3%) and propose a future work to take it into account.

## ACKNOWLEDGEMENTS

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## REFERENCES

ASHRAE. 2002. Guideline14-Measurement of energy and demand savings, American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Atlanta, GA.

ASHRAE. 2013. ASHRAE Fundamentals, American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Atlanta, GA.

DOE. 2013. EnergyPlus 8.0 Input/Output Reference: The Encyclopedic Reference to EnergyPlus Input and Output, US Department Of Energy.

IBPSA. 1987-2013. Proceedings of the IBPSA conferences ('87. '91, '93, '95, '97, '99, '01, '03, '05, '07, '09, '11, ‘13)

Kim, Y.J., Ahn, K.U., Park, C.S. and Kim, I.H. 2013. Gaussian emulator for stochastic optimal design of a double glazing system, Proceedings of the 13th IBPSA Conference, August 25-28, Chambery, France, pp.2217-2224

Morris, M.D. 1991. Factorial sampling plans for preliminary computational experiments, Technometrics, Vol.33, pp.161-174